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Stock Market Forecasting Using ANFIS with OWA Operator

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ABSTRACT

Stock market prediction is very interesting and yet very difficult job. Many techniques have been proposed for the prediction of stock prices. Furthermore, some drawbacks are found in the existing methods Firstly, statistical models are single variable methods and to build them some assumptions are necessary. Secondly, higher dimensional data can not easily processed by existing forecasting models, because model will become more complex with the increase of data dimensions. So to overcome all these drawbacks a new algorithm is proposed in this article, which employs a minimal variability order weighted averaging (OWA) operator to aggregate values of high dimensional data into a single attribute. Based on the proposed model a hybrid network based fuzzy inference system combined with subtractive clustering is used to forecast Bombay Stock Exchange Index (BSE30). Further, the proposed model is compared with some existing models. Results have shown that proposed model gives better forecasting than existing models.

Keywords: Neural Networks, Fuzzy Logic, Forecasting, Stock Market, Subtractive clustering, OWA.

Mathematics Subject Classification (MSC): 68T05, 68T27, 68T35.
Computing Classification System (CCS): I.2.3, I.2.5, I.5.3.

1 Introduction

Stock market forecasting is very important and difficult task in the financial world. Decision makers always try to predict stock prices more accurately. Enormous research has been done in recent times and continues to find an optimal prediction model for the stock market. Most of the forecasting research work has employed statistical methods, such as autoregressive (AR) model (Champernowne, 1948), the Autoregressive Moving Average Model (ARMA) (Avci and Akpolat, 2006), and the autoregressive integrated moving average Model (ARIMA) (Box and Jenkins, 1997). These linear models which are not very adequate in stock market prediction. Later on non-linear techniques, such as Autoregressive Conditional Heteroskedasticity (ARCH) (Engle, 1982) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (Bollerslev, 1986) were proposed to surmount their shortcomings.

Recently, an artificial intelligence (AI) techniques become more popular in prediction problems such as artificial neural networks (ANNs), genetic algorithms(GAs), fuzzy logic , because the complex problems which are difficult to solve by classical methods are easily solved with the help of AI techniques (Chang, Liu and Fan, 2009). These techniques have been successfully used to replace complex mathematical systems for forecasting (Chang et al., 2009; Keles, Kolcak and Keles, 2008; O'Connor and Madden, 2006; Aisjah and Arifin, 2013; Yang, Dawson, Brown and Gell, 2006) and in many other applications (David, Dragos, Bulzan, Precup, Petriu and Radac, 2012; Feriyonika and Dewantoro, 2013). Some researchers attempted to forecast financial time series using improved neural network and fuzzy models (Kodogiannis and Lolis, 2002). Recently, Kim and Lee combined genetic algorithms (GA) with ANNs to improve the generalizability and learning of ANNs for the prediction of stock prices and shown that their proposed model outperforms the linear transformation model (Kim and Lee, 2004). Later on, a state of art of adaptive network-based fuzzy inference system (ANFIS) has presented (Ansari, Kumar, Shukla, Dhar and Tiwari, 2010). ANFIS uses fuzzy ”if-then rules” to formalize the qualitative aspects of human knowledge and also overcome the drawback of ANNs that traditional ANN method is a black box and the rules that are derived from ANN are not easily understandable (Chen, Cheng and Teoh, 2008). In the paper (Joelianto, Canura and Priyanto, 2013), ANFIS is used to improve transient response performance of PID controller. Again a hybrid model based on adaptive-network-based fuzzy inference system was presented to forecast Taiwan stock market (Wei, Chen and Ho, 2011). For the evaluation of purposed model they used six years of period data sets from Taiwan stock exchange (TAIEX) and results have shown that the model performs better then some existing models in literature.

After reviewing the literature we have seen that statistical models, ARMA (Box and Jenkins, 1997), ARCH (Engle, 1982) and GARCH (Bollerslev, 1986), are single variable methods and to build them some assumptions are necessary. In stock market, the relationship between future and past data sets are not necessarily linear. So these statistical models are inefficient with either linear or non-linear relationships (Jilani and Burney, 2008). Secondly, higher dimensional data can not easily processed by existing forecasting models, because model will become more complex with the increase of data dimensions. Moreover the rules laid out by AI techniques used in time series models, such as ANN and GA are quite complex to understand (Hadavandi, Shavandi and Ghanbari, 2010). To overcome these disadvantages of existing models Cheng et al. (Cheng, Wei, Liu and Chen, 2013) uses ordered weighted averaging (OWA) operator given by (Fuller and Majlender, 2001) to reduce the data dimensions. Same researcher also studied computationally complex and decision makers need minimal variability (Cheng et al., 2013). To overcome these drawbacks this study incorporates minimal variability OWA operators (Fuller and Majlender, 2003) and ANFIS technique. The ordered weighted averaging is used to reduce computational complexity of high dimensional data and ANFIS with subtractive clustering is used to produced understandable rules for investors. Our proposed model is implemented and verified through an empirical analysis of the stock data sets, collected from Indian Bombay stock market (BSE30).

The rest of the manuscript is organized as follows: section 2 provides basic terminology and tools. The schematic flow and steps of proposed algorithm is discussed in section 3. Finally experimental results and comparison with existing models are given in section 4 followed by conclusion and future scopes in section 5.

2 Basic terminology and tools

2.1 Order weighted averaging

The OWA first introduced by Yagar (Yager, 1988), has gained much interest among researchers. In recent years, many related studies have been conducted. Fuller and Majlender (Fuller and Majlender, 2001) use Lagrange multipliers to solve constrained optimization problem and determine the optimal weighing vector. Fuller and Majlender (Fuller and Majlender, 2003), employ the Kuhn-Tucker second order sufficiency conditions to optimize and derive OWA weights.

2.1.1 Yagar's OWA

Yagar (Yager, 1988), proposes an OWA to get optimal weights of the attributes. An OWA operator of dimension n is a mapping $f : R^n \to R$ that has an associated weighting vector $W = [w_1, w_2, ..., w_n]^T$ with the following properties:

$w_i \in [0, 1]$ for $i \in I = \{1, 2, 3, ..., n\}$ and $\sum_{i \in I} w_i = 1$ such that

$$f(a_1, a_2, ..., a_n) = \sum_{i \in I} w_i b_i, \tag{2.1}$$

where b_i is the ith largest element in the collection of the aggregated objects $a_1, ..., a_n$.

In (Yager, 1988), Yagar introduced two important characterizing measures associated with the weighting vector W, i.e, measure of orness and measure of dispersion, which are defined as follows:

$$\text{orness}(W) = (1/n - 1) \sum_{i=1}^{n} ((n - i) * w_i), \tag{2.2}$$

where orness$(W) = \alpha$ is a situation parameter.

$$\text{disp}(W) = - \sum_{i=1}^{n} w_i ln w_i. \tag{2.3}$$

The orness measure has the following properties:

$W = \{w_1, w_2, ..., w_n\}$ is the weight vector of an OWA with orness$(W) = \alpha$.

Then, $W' = \{w_n, w_{n-1}, ..., w_1\}$ is the reverse order of W, orness$W' = 1 - \alpha$.

2.1.2 Fuller and Majlender's OWA

Fuller and Majlender (Fuller and Majlender, 2003) transform Yagar's OWA equation to a polynomial equation by using Kuhn-Tucker second order sufficiency conditions. According to their approach, the associated weight vectors can be obtained as:

firstly the interval $(0,1)$ is partitioned by the following equation

$$(0,1)=\bigcup_{r=2}^{n-1} J_{r,n}\cup J_{1,n}\cup\bigcup_{s=2}^{n-1} J_{1,s}, \tag{2.4}$$

where

$$J_{r,n}=\left(1-\frac{2n+r-2}{3(n-1)},1-\frac{2n+r-3}{3(n-1)}\right],\ r=2,...,n-1,$$
$$J_{1,n}=\left(1-\frac{2n-1}{3(n-1)},1-\frac{n-2}{3(n-1)}\right),$$
$$J_{1,s}=\left[1-\frac{s-1}{3(n-1)},1-\frac{s-2}{3(n-1)}\right),\ s=2,...,n-1.$$

When $\alpha\in J_{r,s}$ then

$$W^*=(0,...,0,w_r^*,...,w_s^*,0,...,0)^T, \tag{2.5}$$

where

$$w_j=0 \text{ if } j\notin I_{\{r,s\}},$$
$$w_r^*=\frac{2(2s+r-2)-6(n-1)(1-\alpha)}{(s-r+1)(s-r+2)},$$
$$w_s^*=\frac{6(n-1)(1-\alpha)-2(s+2r-4)}{(s-r+1)(s-r+2)},$$
$$w_j^*=\frac{s-j}{s-r}w_r+\frac{j-r}{s-r}w_s \text{ if } j\in I_{\{r+1,s-1\}},$$

where $I_{\{r+1,s-1\}}=r+1,...,s-1$.
If $r=1$ and $s=n$ then, $\alpha\in J_{1,n}$, and

$$W^*=(w_1^*,...,w_n^*)^T, \tag{2.6}$$

where

$$w_1^*=\frac{2(2n-1)-6(n-1)(1-\alpha)}{n(n+1)},$$
$$w_n^*=\frac{6(n-1)(1-\alpha)-2(n-2)}{n(n+1)},$$
$$w_j^*=\frac{n-j}{n-1}w_1+\frac{j-1}{n-1}w_n \text{ if } j\in 2,...,n-1.$$

2.2 Subtractive Clustering

Subtractive clustering is a type of fuzzy clustering was developed by Chiu (Chiu, 1994) for the estimation of initial location and number of cluster centers. Let n is the collection of data points $x_1,x_2,...,x_n$ in a M dimensional space. Each data point is considered as a potential cluster center. The potential of data point x_i is defined as:

$$P_i=\sum_{j=1}^{n}\exp^{-\frac{4\|x_i-x_j\|^2}{r_a^2}}, \tag{2.7}$$

where, the symbol $\|.\|$ denotes the Euclidean distance and r_a is the radius defining a neighborhood.
After computing the potential of each data point, highest potential data point is chosen as the first cluster center. Let P_1^* be the potential value of the first cluster center x_1^*. The potential P_i is revised for each data point x_i to generate the other cluster centers by using the formula:

$$P_i = P_i - P_1^* \exp^{-\frac{4\|x_i - x_1\|^2}{r_b^2}}, \tag{2.8}$$

where, the constant r_b is the new radius which we get after revising the potential of all the data points. After revising the potential of data points, select the second cluster center having highest remaining potential. This process continues until a sufficient number of clusters are obtained.

2.3 Framework of ANFIS

ANFIS is a fuzzy inference system implemented in the framework of adaptive networks (Jang, Sun and Mizutani, 1997). By using a hybrid learning procedure (Jang, 1993), the ANFIS can construct an input-output mapping based on both human knowledge in the form of fuzzy *"if-then"* rules and stipulated input-output data pairs. It integrates the desirable features of both fuzzy system and neural networks. For simplicity, we assume that the fuzzy inference system under consideration has two inputs x, y and one output f_{out}. For the first order Takagi-Sugeno fuzzy model, two fuzzy *"if-then"* rules are as follows:
Rule 1: If x is A_1 and y is B_1 then $f_1 = p_1 x + q_1 y + r_1$,
Rule 2: If x is A_2 and y is B_2 then $f_2 = p_2 x + q_2 y + r_2$,
where p, q, and r are the parameters. The ANFIS architecture with two inputs and one output is shown in Figure 1.

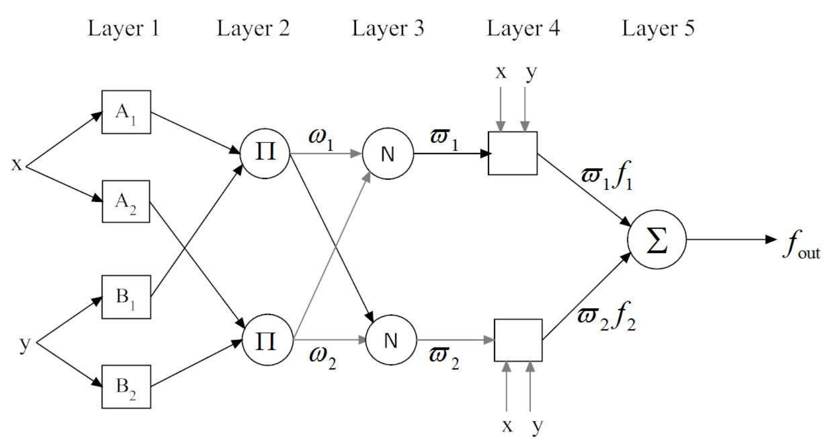

Figure 1: ANFIS Architecture

Layer 1: Every node i in this layer is a square node with node function

$$O_{1,i} = \mu_{A_i}(x), \text{ for } i = 1,2 \quad (2.9)$$
$$O_{1,i} = \mu_{B_{i-2}}(y), \text{ for } i = 3,4 \quad (2.10)$$

where x, y are the inputs to node i, A_i (B_{i-2}) is a linguistic labels for inputs. In other words $O_{1,i}$ is the membership grade of A_i (B_{i-2}). Normally membership function for $\mu_{A_i}(x)$ and $\mu_{B_{i-2}}(x)$ are chosen to be generalized bell function:

$$\mu_{A_i}(x), \mu_{B_{i-2}}(y) = \frac{1}{1 + |\frac{x-c_i}{a_i}|^{2b_i}}, \quad (2.11)$$

where a_i, b_i, c_i are the parameters of membership function. These are also known as the premise parameters.

Layer 2: Every node in this layer is a circular node labeled $\prod$, whose output is the product of all the incoming signals:

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_{i-2}}(y), \quad i = 1, 2; \quad (2.12)$$

each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is circular node labeled N. The ith node calculates the ratio of the i-th rule's firing strength to the sum of firing strengths of all the rules:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \quad (2.13)$$

Layer 4: Every node i in this layer is a square node with a node function

$$O_{4,i} = \overline{w_i}.f_i, \quad i = 1, 2; \quad (2.14)$$

where w_i is the output of layer 3.

Layer 5: This is a single circular node labeled $\sum$, which computes the overall output as the summation of all incoming signals:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} = f_{out}. \quad (2.15)$$

3 Steps of proposed algorithm

This paper proposes a new model that combines OWA (Fuller and Majlender, 2003), subtractive clustering and ANFIS. MATLAB (R2008a) software is used for the coding and simulation process. The overall schematic flowchart of the proposed model is shown in Figure 2 which includes the reduction of data dimensions by using OWA operator and implementation of ANFIS model for the forecasting of stock market in step second.
The algorithm of the proposed model is given as follows:

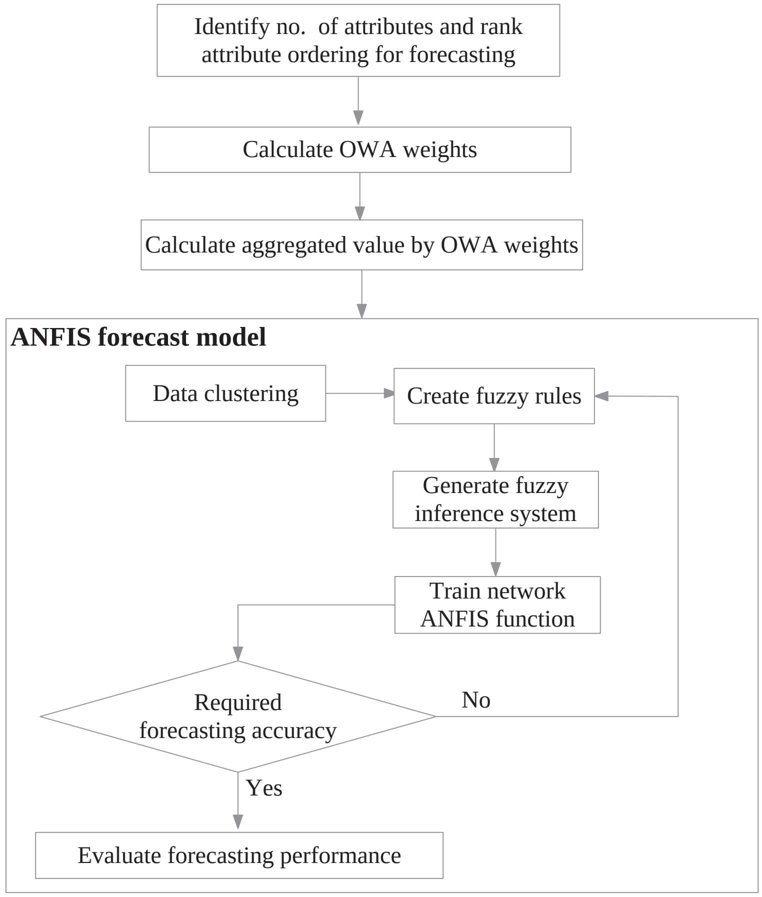

Figure 2: Proposed Schematic Flow

Step 1: Identify the number of attributes for forecasting the future price:
Three periods of stock price, $S(t-2)$, $S(t-1)$ and $S(t)$ are used to forecast the future price $S(t+1)$. So we have three attributes for the prediction process.

Step 2: Calculation of OWA weights:
Here in this step, we calculate the OWA weights by using the Eqs.(2.4-2.6). (Several α values, ranging from 0.1 to 0.5 are used to construct unlike sets of OWA weights.)
$\alpha = 1 - \alpha$ if $\alpha > 0.5$
Here each α value represents one set of influence degrees. The influence degrees of stock prices are given in Table 1.

Step 3: Aggregate value calculation:
In this step, by one linear equation, which is given as:

$$A(t) = W_1 \times S(t) + W_2 \times S(t-1) + W_3 \times S(t-2). \tag{3.1}$$

where W_1, W_2 and W_3 denotes influence degrees of stock prices for the three recent periods $S(t)$, $S(t-1)$ and $S(t-2)$. $A(t)$ denotes the aggregated value of stocks with corresponding degrees of influence.

Table 1: For $n = 3$ OWA weights

	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.4$	$\alpha = 0.5$
W_1	0.0	0.0333	0.1333	0.2333	0.3333
W_2	0.2	0.3333	0.3333	0.3333	0.3333
W_3	0.8	0.6333	0.5333	0.4333	0.3333

Step 4: Clustering of data:
Now we cluster the data set by using subtractive clustering method for the generation of fuzzy rules. As we explain in the section 2.2 that every data point in subtractive clustering has a potential cluster center. Based on the density of surrounding data points a measure of the likelihood for each data point has been calculated that would define the cluster center. The value of Radii varies between 0 and 1 and defines the cluster size in each of the data dimensions. We set range of influence = 0.47, squash= 1.25 accept ratio = 0.5, reject ratio = 0.15.

Step 5: Identify the type of membership function for input and output variables :

Since $A(t)$ is the only aggregated value which is used as input variable. For this input, subtractive clustering generates three Linguistic intervals (explained in Step 4) and we have set gaussian membership function for input. To develop a output linguistic variable only one type of membership function is used corresponding to three linguistic intervals generated by subtractive clustering. Now fuzzy if-then rules are generated by using Takagi-Sugeno fuzzy model with three inputs and one output, the description of generated fuzzy rules are given as follows:
if $x(A(t)) = A_i$ *then* $f_i(S(t+1)) = p_i x + r_i$
where $x(A(t))$ denotes linguistic variable, A_i gives the linguistic value, f_i announces the i-th output and p_i, r_i are the parameters $(i = 1, 2, 3)$.
Step 6: Generate fuzzy inference system:
Three linguistic intervals (low, medium, high) for input are obtained by subtractive clustering and membership functions for input and output are set in the previous Step. The input linguistic intervals are used in the ”if” condition part and output membership function is in the ”then” condition part. The rules generated by fuzzy inference system are given as follows:
Rule 1. if $x(a_j) = A_{low}$ *then* $f_{low}(t+1) = p_{low}x + r_{low}$
Rule 2. *if* $x(a_j) = A_{mid}$ *then* $f_{mid}(t+1) = p_{mid}x + r_{mid}$
Rule 3. *if* $x(a_j) = A_{high}$ *then* $f_{high}(t+1) = p_{high}x + r_{high}$
where A_i denotes linguistic values, $x(a_j)$ denotes the linguistic variables, $f_i(t+1)$ is the i-th output value and p_i, r_i are the parameters.

Step 7: Training of parameters:
After the formation of fuzzy ”if-then rules”, the combination of back propagation gradient-decent and least-square method is used in the training process of proposed model. The training data sets are used to find the more efficient parameters for the fuzzy inference system to get more accurate results. To improve the input parameters, ANFIS used gradient-decent method and for output parameters, ANFIS used least-square method.

Table 2: Comparison of different models in terms of RMSE

Models		2006	2007	2008	2009	2010	2011	2012
Chen's model(Chen, 1996)		138	156	188	177	113	167	110
ANFIS(Jang, 1993)		120	136	178	172	102	155	92
Proposed model	$\alpha = 0.1$	**37**	**45**	**77**	**56**	**34**	**45**	**33**
	$\alpha = 0.2$	68	83	158	105	62	84	64
	$\alpha = 0.3$	91	105	190	140	81	113	79
	$\alpha = 0.4$	117	134	244	177	105	146	100
	$\alpha = 0.5$	140	164	292	217	124	181	121

For example, for the year 2012 rule 1 parameters are shown as follows:
$p_{low}, r_{low} = 1.004, -71.83$

Step 8: The proposed model for forecasting the future price:
After obtaining the optimal membership functions, train the data set along with optimal fuzzy rules and membership functions in the testing data set for the prediction of future price $S(t+1)$.

Step 9: Evaluation of prediction performance:
To compare the performance of proposed model with the existing models, RMSE is chosen as evaluation criterion defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} |actual(t) - forecast(t)|^2}{n}} \tag{3.2}$$

where actual(t) refers the actual value of data, forecast(t) refers the predicted value and n is the total number of data entries.

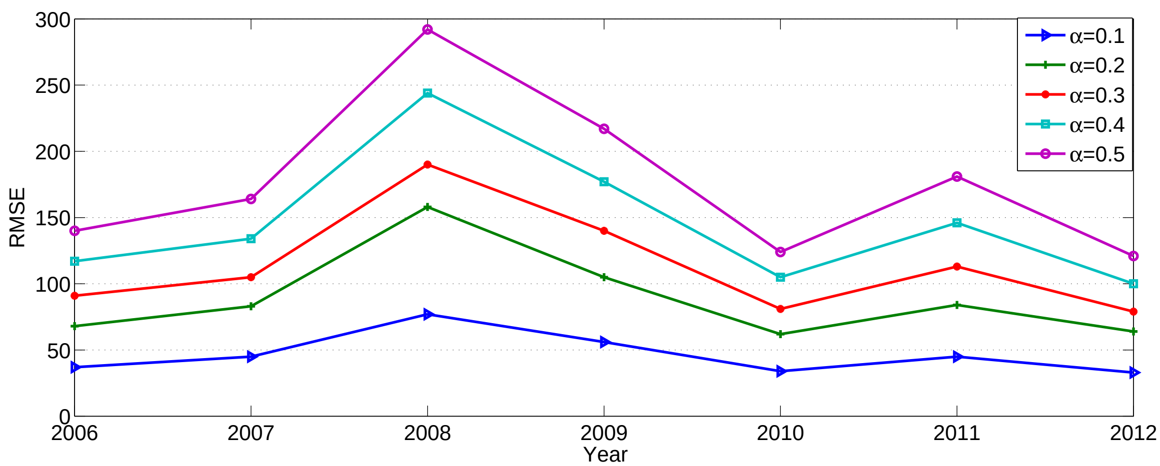

Figure 3: Performance comparison of proposed model for different α values in terms of RMSE

4 Experimental results

We collect data from Bombay Stock Exchange index BSE30, from the period 2006 to 2012. We used every year data set of BSE30 as one complete verification for prediction. There are almost 240 to 260 trading days in each year. So, we use first 200 days as training data set and the rest as testing data set. Also, we compare proposed model with Chen's (Chen, 1996) and ANFIS (Jang, 1993) models.

There are seven testing data sets each corresponding to a particular year, so total thirty forecasting performance records for different values of α ranging from 0.1 to 0.5 are shown in Table 2. In the same table a comparison in terms of RMSE of proposed model with Chen's (Chen, 1996) and ANFIS (Jang, 1993) models are presented. Corresponding to the value $\alpha = 0.1$ proposed model gives the best performance among the listing models with the minimum RMSE value (see Table 2). The comparison of different values of α is shown in Figure 3. In addition, a comparative analysis of the forecast RMSE obtained from the proposed model and existing models is shown in Figure 4. Which shows that the average performance of the proposed models is better than the compared models. The computational complexity of proposed model is less as compared to the listing models, because the data is partitioned by employing a clustering technique which helps to generate simple three linguistic fuzzy rules. On the other hand, this is not possible in most of the other existing models.

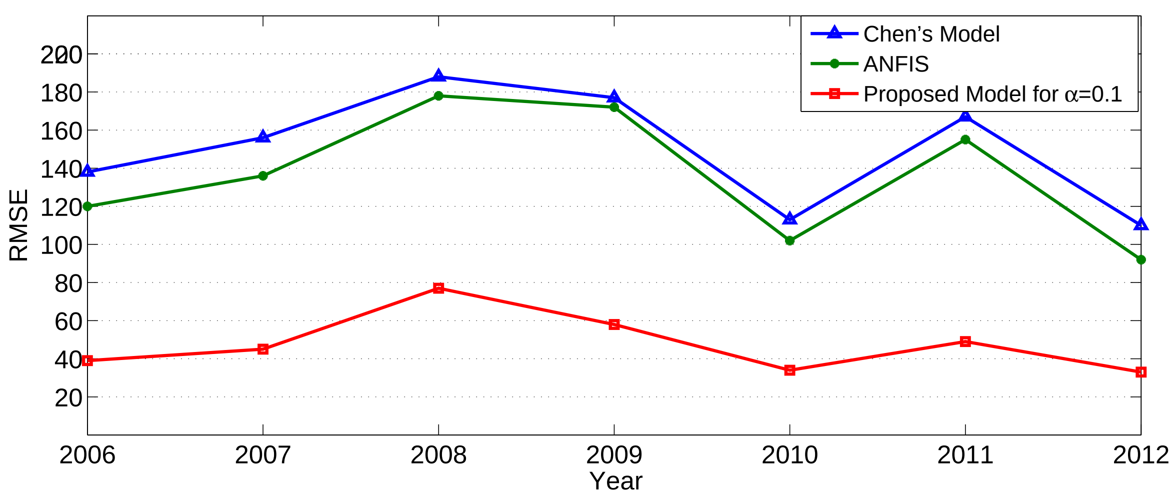

Figure 4: Performance comparison of different models in terms of RMSE

5 Conclusion

It is not easy to predict stock trends because many complex components influences stock market. Stock investors, decision makers and financial analysts try to forecast stock market more precisely. In this study, we developed a new time series model combining minimal variability OWA operator to aggregate high dimensional data into a single useful forecasting factor and ANFIS with subtractive clustering for forecasting stock prices. From the experimental results it has been shown that the proposed model outperforms some listed models. Further the results of this paper can be very useful for stock investors and decisions makers such as the power of the decision making can be extended with the use of minimal variability OWA operator, as they can adjust the weights according to the situation of the decision maker.

Some of the limitations of our algorithm are, firstly, no preprocessing of data (i.e., does not filter the noisy data) and secondly, a fixed clustering technique is used, which may not the best algorithm for all data sets. In future these results can be further improved, using some preprocessing techniques for noise reduction, other clustering algorithm with optimization functions and optimization of the ANFIS parameters using genetic algorithms for better forecasting results.

The proposed model generates only three linguistic rules, substantially reducing its computational complexity. It is also observed that the BSE30 index depend on last three days indices. Hence the BSE30 index has longer observation period.

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